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Acceptability of robotic manipulators in shared working environments through human-like redundancy resolution

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A B S T R A C T

Next generation robotic manipulators are expected to resemble a human-like behavior at kinematic level, in order to reach the same level of dexterity of humans in operations like assembly of small pieces. These manipulators are also expected to share the same working environments with humans without artificial barriers.

In this work we conjecture that making robots not only kinematically similar but also able to move and act in the same way as humans do, might facilitate their social acceptance. For this the kinematic redundancy of such new generation manipulators can be exploited. An experimental campaign has been organized to assess the physiological comfort/discomfort perceived by humans working side-by-side with robots. For comparison, a human-like and two alternative redundancy resolution strategies have been implemented. The analysis confirmed the hypothesis that a human-like motion of the robot helps in facilitating social acceptance, by reducing the perceived stress by humans in human-robot coexistence.

1. Introduction

Despite the availability of humanoid robotic platforms, their social acceptance is still a challenging open issue. First studies like the so-called "uncanny valley" proposed in (Mori, 1970) (see Fig. 1) or the one proposed in (Kaplan, 2004), agree in classifying the social integration of robots in human environments as a non-trivial task.

In industrial environments, where humanoid robots might be adopted to complement human labor, the problem of integrating humans and robots in the same workspace might turn to be even more challenging. Human-robot cooperation should not just be physically safe, (De Santis et al., 2008), but also psychologically comfortable to the humans. Beside the human-like appearance of robots, which is discussed e.g. in (Hwang et al., 2013), a better and natural cooperation could be achieved if humans are, at all times, assured that they understand what the robot's intentions are, and that the robot executes its tasks with motion profiles that humans perceive as safe, (Kulic and Croft, 2007a). This requirement must comply with the production constraints, which require an accurate task execution.

The availability of many degrees of freedom (DOF) might facilitate the achievement of all these requirements. Humanoid robots are in fact redundant manipulators (i.e. composed by robotic arms having more DOF than those strictly necessary to perform a certain task) and are, in principle, able to cooperate with humans in the same way as humans co-operate with co-workers. In fact, since the same task can be performed in several ways without any task performance degradation, redundant manipulators offer a wide range of flexibility in motion planning. Besides optimizing some performance criteria (energy consumption, manipulability, distance from joint limits, etc.) redundancy can be exploited to synthesize (i.e. reproduce with an articulated manipulator) the motion of human arms. The motion of the human arm has already been investigated in several prior works, ranging from pure kinematic approaches to more complicated neuromuscular analyses, often with focus on redundancy resolution. A brief review of related studies will be given in the Section 2.

From an ergonomics standpoint, in view of the layout of new production lines populated by both robotic manipulators and human operators, it is important to assess in an objective way the impact of different redundancy resolution techniques to the psychological state of nearby humans. Assessment of the quality of the HRI by measuring the affective state of humans is an interesting and emerging topic. A survey of physiological methodology to assess the quality of the HRI is given in Section 2.

This paper contributes to these issues by discussing a methodology which has been used to analyze the affective state of humans working side-by-side with human-like robotic manipulators, as a function of the strategy used for redundancy resolution.

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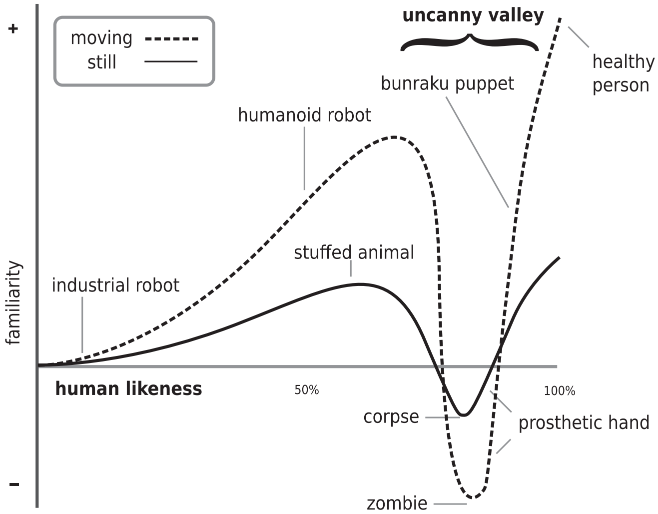

Fig. 1. The so-called "uncanny valley" (source Wikipedia), an intuitive correlation between robots' human-likeness and their social acceptance; this correlation is positive until a certain thresholds, called the *uncanny valley* where such correlation becomes negative.

Experiments have been performed on 18 volunteers whose physiological response to different motions of the robot has been measured using a dedicated instrumentation and a well-defined protocol. Data have been analyzed using statistical tools. As a result, it is shown that there is a clear correlation of the emotional state of the volunteers with the adopted redundancy resolution criterion. We believe that the methodology described in this paper and the related outcome represent a significant contribution in the field of assessment of human–robot interaction, and may open the way to more articulated methodologies to study ergonomic issues of the envisaged future production lines, populated by both humans and robots.

The remainder of this work is organized as follows. In Section 2 some background material on human motion analysis and synthesis, as well as on state of the art methodologies to assess the affective state of human volunteers is presented. Section 3 describes the experiments performed to gather all the physiological data needed for subsequent analyses as well as the methodology adopted to post-process the acquired data. Section 4 describes factual results from the statistical analysis, while Section 5 finally discusses their interpretation.

2. Background

This Section presents a brief overview of state of the art methodologies to analyze and synthesize human-like motion profiles. Current methodologies to measure the affective state of humans are also described.

2.1. Human motion analysis and synthesis

Pioneers of neurophysiological studies proposed the existence of neural strategies to explain human motion control, (Bernstein, 1967). These concepts, well-known nowadays and referred to as *synergies*, were later refined and exploited in different works to explain natural grasping postures (Santello et al., 1998), reaching movements (Sabatini, 2002), whole body postures as in (Terres-Oviedo and Ting, 2007), etc.

Apart from the neuroscience literature, the research communities of information technology, automatic control, optimization, and biomechanics, are very active in the field, as well. In this context, the pioneer work (Hogan, 1984) presented the first results in modeling natural trajectories for the human arm as resulting from a jerk minimization criterion. Further research led to more detailed objective functions.

Recently, in (Khatib et al., 2009), a biomechanics-based investigation has been performed, where the muscular redundancy has been explicitly taken into account. It was argued that in a static configuration, among all the possible muscular activations, the optimal posture can be predicted using a weighted least-square approach.

Finally, from ergonomic studies on the arm posture, in (McAtamney and Corlett, 1993) an index called RULA to measure the discomfort of a particular arm posture has been proposed. The same index has been recently exploited to obtain a shorter and more natural-looking motion for the dual-arm anthropomorphic robot Justin developed at the DLR (German Aerospace Center), see (Zacharias et al., 2011).

In previous works from the same authors of the present paper, see (Zanchettin et al., 2011), a model describing the natural way humans adopt to resolve arm redundancy has been identified. Based on motion capture experiments, we performed a nonlinear correlation analysis between the hand pose (position and orientation) $\boldsymbol{\mu}$ and the elbow swivel angle α, see (Kreutz-Delgado et al., 1990), resulting in the following model

$$\begin{aligned}\alpha &= p(\boldsymbol{\mu})\\ &= 0.88\cos(\theta+2.30)-0.40\cos(\rho+\theta)\\ &\quad +0.49\cos(\theta+\phi+2.98)-1.39-0.21\mathrm{atan2}(z,y)\\ &\quad -0.64\sin(\rho)-0.50\mathrm{atan2}(y,x)-0.22\cos(\rho+\theta+\phi)\\ &\quad +0.47\cos(\phi+0.60)-0.15\mathrm{atan2}(z,x)\\ &\quad +0.34\cos(\rho+\phi+1.07) \qquad (1)\end{aligned}$$

which relates the right elbow swivel angle with the Cartesian coordinates of the right hand x,y,z and the Euler angles ρ,θ,ϕ, respectively. While the analysis of the human motion was intentionally performed for future used in a robotic controller, as discussed in (Zanchettin et al., 2012), the quality of the HRI arising from these particular motion primitives had not yet been addressed.

2.2. Affective state assessment

In this Section, a short survey[1] of existing methodologies to measure the affective state, with particular emphasis on quality of the HRI, is presented.

Although a well-established methodology to analyze emotions is not yet available, a commonly adopted framework to represent the emotional state of individuals has been presented in (Lang et al., 1993). The author proposes a characterization of affective experiences in terms of two main categories: valence and arousal. Valence represents the pleasantness of stimuli, with positive (or pleasant) at one end and negative (or unpleasant) at the other end. The other dimension is called arousal (activation level) which corresponds to the state of being awake or reactive to stimuli. The different emotional labels can be plotted at various positions on a 2D plane spanned by these two axes to construct a 2D emotion model, see e.g. (Lang, 1995), as sketched in Fig. 2.

Statistical correlations of different physiological signals ranging from the heart or respiration rates to the skin conductance or the

[1] The reader is referred to (Mauss and Robinson, 2009) for a more exhaustive survey.

brain electrical activity with an individual's arousal/valence state have been intensively studied, see e.g. (Lang, 1995; Jacobs et al., 1994; Bradley and Lang, 2000b; Kim and Ande, 2008).

To some extent, the "uncanny valley" sketched in Fig. 1 was the first attempt to throw a bridge between robotics and psychology. Pioneers of this field were Kulic and Croft, whose studies laid the basis to the robotics community on the measurement of the affective state of individuals working side-by-side with robots using physiological devices, see (Kulic and Croft, 2007a). This concept has been further addressed e.g. in (Bartneck et al., 2008) or (Dehais et al., 2011).

In studies aimed at measuring the robot-induced stress on humans during coexistence, see e.g. (Kulic and Croft, 2007b), three physiological signals are usually acquired: HR (heart rate), EMG (electromyography), and SC (skin conductance). The typical use of such physiological signals in the field of affective state assessment is briefly reviewed in the following, see also (Bethel et al., 2007).

2.2.1. Heart rate

The absolute value of the heart rate is strongly influenced by several factors such as, for instance, physical fitness and posture. Its variability (HRV) is widely used in the medical literature and can be addressed either in time- or frequency-domain. The time-domain analysis typically reveals the arousal state related to hear rate accelerations or decelerations, see (Bradley and Lang, 2000b). The frequency-domain analysis of the HRV is typically based on spectral decomposition, see (Malik, 1996; Cohen et al., 1999). Compared with the time-domain analysis, the frequency-domain analysis of the HRV can reveal a more detailed information about the ongoing neural activities. In fact, the heart rate is modulated in response to a variety of stimuli by both the parasympathetic and the sympathetic nervous systems. While the former is responsible for a physiological response to normal situations, the latter is more related to reactions to external stimuli producing anxiety, stress and warnings. Several scientists agree on the well-defined frequency separation between the sympathetic- and the parasympathetic-related activities on the HRV power spectral density (PSD), see e.g. (McCraty et al., 1995; Delaney and Brodie, 2000). In particular, LF (Low Frequency) bandwidth of the HRV PSD, approximately in the range $0.04 - 0.15$ Hz, are related to the sympathetic activities, while the HF (High Frequency) bandwidth, between 0.15 and 0.5 Hz, are dominated by the parasympathetic nervous system. As for the correlation of the HRV with the affective states, scientists somehow agree in relating physiological stress and negative valence with an increased LF to HF ratio, see (McCraty et al., 1995; Delaney and Brodie, 2000).

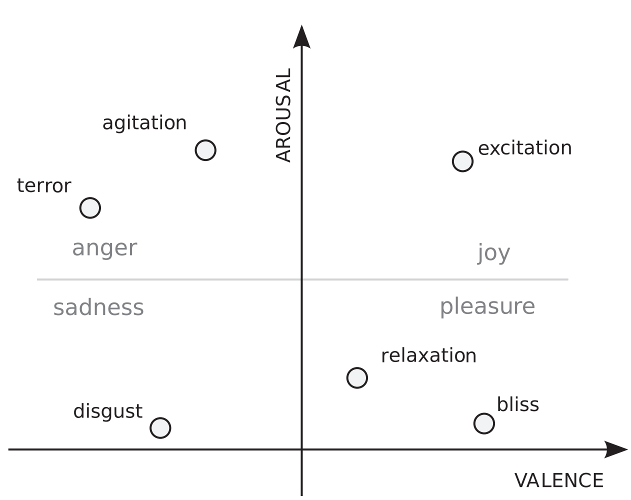

Fig. 2. Two-axes representation of the affective state, adapted from (Kim and Ande, 2008).

2.2.2. Surface electromyography

Surface facial electromyography is a non-invasive technique to assess the affective state of individuals subject to external stimuli of different nature, ranging from visual, (Lang et al., 1993), to acoustic, (Bradley and Lang, 2000a), ones. More recently, it has been also adopted to analyze the emotional state while playing at computer games, as in (Ravaja et al., 2008), or to address the quality of the human–robot interaction (Kulic and Croft, 2007a).

The analysis of the EMG signal is definitely less involved than the one adopted for the ECG signal, however a variety of different methods exist, ranging from the integrated EMG signal, as explained in (Jorge and Hull, 1986), to spectral analysis, see e.g. (Lindstrom et al., 1970). As for the correlation with the affective state, it is agreed that facial EMG activities are related to unpleasant emotions, (Bradley and Lang, 2000b; Codispoti et al., 2001; Larsen et al., 2003).

2.2.3. Electrodermal activity

Skin conductance (SC) is widely used for affective state estimation.

The SC signal includes two types of electro-dermal activity: the DC level component and the skin conductance response (SCR). The DC level in the SC signal, or skin conductance level (SCL), indicates the general activity of the perspiratory glands influenced by body temperature or external temperature, (Kim and Ande, 2008), while fluctuations around the average level are due to sweat secretion initiated by distinct bursts of sudomotor nerve activity, which result from the liberation of acetylcholine by the sympathetic nervous system, (Boucsein, 1992). In turn, SCR is usually adopted as an indicator of the activation level in response to stimuli (Bach et al., 2010b; Khalfa et al., 2002). Usually, the SC exhibit a significant drift and several researchers prefer to account for its variability by high-pass filtering the acquired signal, (Kulic and Croft, 2007a). Temporal characteristics of the SCR signal (latency, rise time, amplitude, recovery time, etc.) and their analysis, see e.g. (Bach et al., 2010a), are usually adopted to analyse discrete or short events, (Boucsein, 1992; Khalfa et al., 2002; Dawson et al., 2007). In turn, tonic levels of electrodermal activity over long-duration (e.g. >1 minute) and persistent stimuli, see e.g. (Krumhansl, 1997).

3. Materials and methods

We here conjecture that making robots not only kinematically similar, but also able to move and act in the same way as humans do, might facilitate their social acceptance. The experiments described in the following were aimed at capturing the physiological comfort/discomfort of humans working side-by-side with the robot. No physical interaction or cooperation with the robot was expected.

In the following a detailed description of the experiments (participants, equipment, protocol and data processing) is given.

3.1. Participants

Eighteen healthy male subjects of age 26.7 ± 4.6 have been selected within master students and the research personnel at Politecnico di Milano. They have been recruited without any remuneration using the Department mailing list. All participants were right-handed. Subjects were instructed to abstain from alcohol, caffeine, and nicotine for 2 h before testing.

3.2. Experimental setup

A workspace resembling a working environment has been assembled. The dual-arm prototype robot ABB Frida, see e.g. (Kock et al., 2011), has been placed in the middle of the table and a working station has been setup on the left, next to the robot. The overall setup is shown in Fig. 3. In order to test the physiological response to different robot trajectories, three redundancy resolution criteria have been designed and implemented within the robotic controller, using the native programming language. The first one corresponds to the human-like (HL) kinematic control strategy, derived from (1) and extended to the left arm by exploiting the symmetry of the human body (and of the robot prototype). The second one (non human-like, nHL) has been selected in order to enforce a different correlation between the hand pose and the elbow angle. In other words, two functions $p(\cdot)$, one for the right arm, the other for the left arm, different from the identified ones in (1), have been selected. The last one corresponds to a non human-like time varying (nHLTV) redundancy resolution criterion which has been designed by assigning (without any specific criterion) a time-dependent value to the elbow angle. Figs. 4 and 5 report snapshots from the three motions and the time histories of the left elbow swivel angle, respectively. As one can see from Fig. 5, the nHLTV motion is characterized by a more jerky profile, whilst the nHL is in turn characterized by higher elbow elevations.

The three different trajectories were covered in exactly the same time interval, since the only difference is the redundancy resolution criterion. Moreover, during the three motions, the robot performed exactly the same task, i.e. with the same end-effector movements at the same speed. The task was designed to resemble typical assembly operations, with typical human-like velocities. The only difference between the three executions was only in the so called *null-space* of the task, i.e. in the portion of the joint space which does not entail motion of the end-effector.

The ProComp Infiniti system from Thought Technology was used to acquire the physiological data. The heart muscle activity was measured via ECG (ElectroCardioGraphy) measurement using EKG Flex/Pro sensor. The SCR (Skin Conductance Response) was measured using the SCFlex-Pro sensor. The activity of the corrugator muscle was measured with the MyoScan Pro surface EMG (ElectroMioGraphy) sensor. The sampling frequency was 2048 Hz for the ECG signal and 256 Hz for both the SCR and EMG signals.

The EMG electrodes were arranged in the abdominal placement and fixed with steucoplastic tape to limit the effects of artifacts. The EMG tripolar electrode has been placed on the frontalis muscle, with the reference electrode on the sagittal plane and the two measurement electrodes to measure the activity on the muscle fibers closest to the robot, just above the eyebrow. The SCR probes have been placed on the first phalanges of the digitus secundus (pointer finger) and of the digitus annularis (ring finger), respectively, of the hand closest to the robot.

Fig. 3. Setup for the physiological experiments.

3.3. Procedure

Before the experiments, volunteers were asked to sign a form where they agreed to allow the researchers to collect physiological data. Each volunteer was assigned a coded identity label, which was used to mark these data. Their actual personal details, except from the age, were not recorded.

The researchers then explained the purpose of the experiments reading the following text:

This experiment is part of the EU FP7 project ROSETTA. We organized this experimental campaign to address the problem of physiological stress during human–robot coexistence. The experiments are aimed at investigating the reactions of subjects to robot trajectories. During the experiments no physical interaction with the robot is expected. Please stand relaxed and possibly avoid strong voluntary movements. Physiological data (ECG, EMG and SCR) will be acquired with medical instruments.

The researchers prepared the volunteer attaching ECG, EMG and SCR probes and checked their correct behaviour by asking the volunteer to contract three times the corrugator muscle. The researchers then checked the correct alignment of the volunteer to the table and asked him to place his hands on the table and to get a comfortable and relaxed position.

Approximately 180 *s* of physiological data have been acquired before triggering the robot motion, of which the last 10 *s* will be regarded as baseline for subsequent analyses. Then, the assembly-like task and the corresponding redundancy resolution were activated. The robot performed three cycles (one for each type of redundancy resolution). During each cycle the assembly task was repeated twice with the same redundancy resolution scheme. The total duration of the motion was approximately 120 *s*, while the total duration of one session (including instructions, sensors arrangement, and setup) was about 10 min.

Notice that each subject experienced the three redundancy resolution methods in different sequence in order to remove the possible effects of prior experiences of the robot motion, which may influence and bias the measurements, as pointed out in (Bartneck et al., 2008).

A short interview was finally taken to collect subjective impressions from the volunteer, concerning the perceived safety, naturalness of the robot motion and an estimate of the emotional state (boredom, anxiety, etc.).

3.4. Measurements and post-processing

This Section describes the procedure adopted to extract relevant features from the raw acquired signals. Particular attention was paid to minimize the effect of artifacts, which might invalidate subsequent analyses.

3.4.1. Processing of the ECG signal

From raw ECG data, a filter was applied in order to recognize QRS complex and estimate the time instant corresponding to the R peak. Therefore, the output signal is simply a train of pulses, corresponding to the depolarization of the left ventricular, which is responsible of the R peak in the ECG waveform. Then, the time interval between the subsequent R peaks (called RR interval) was

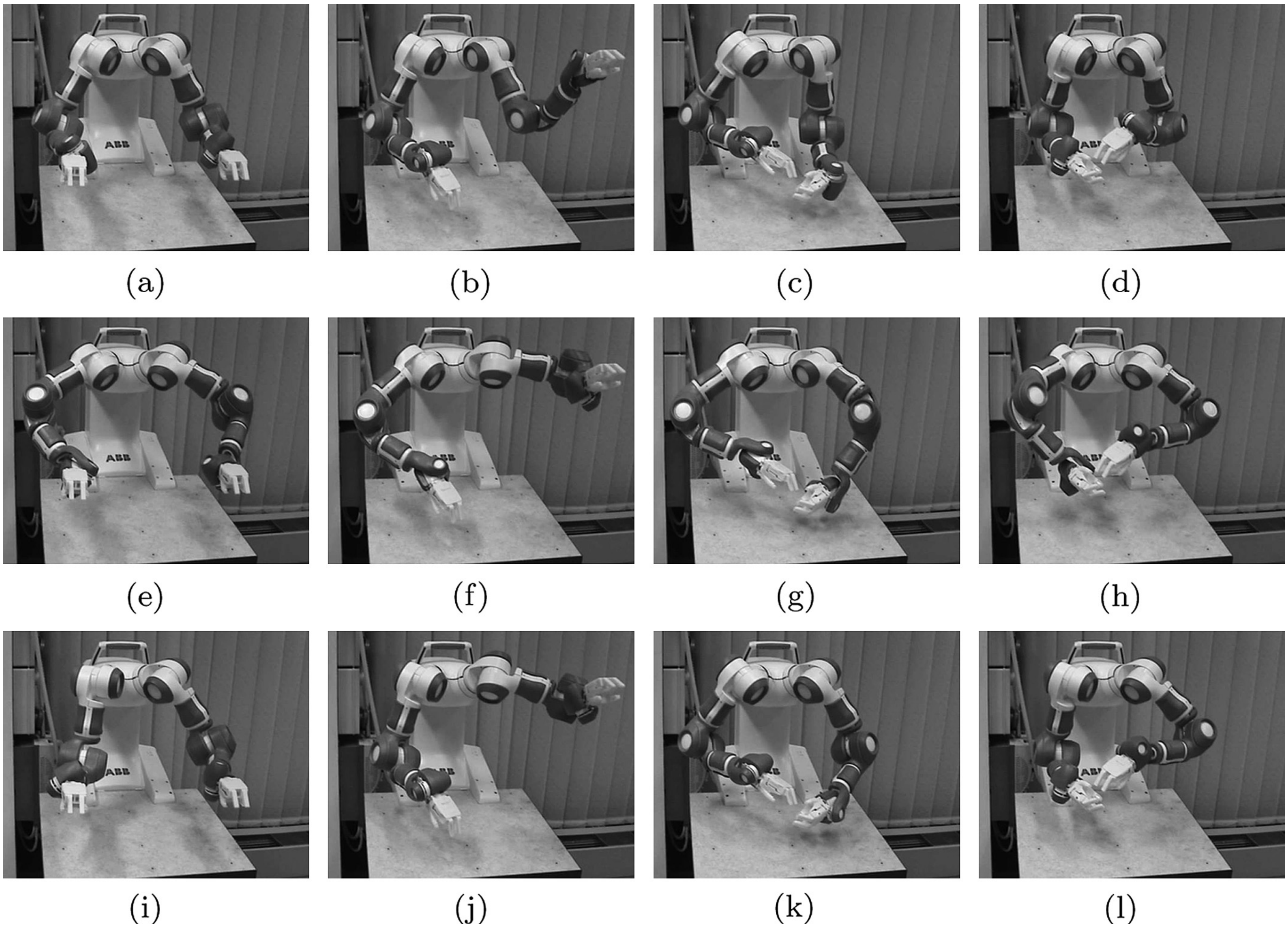

Fig. 4. Three redundancy resolutions for the prototype robot (first row: HL, second row: nHL, third row: nHLTV).

measured. The resulting discrete time signal, updated at the end of each RR interval, is usually called *tachogram*. Spline interpolation has been finally applied to increase the time resolution of the tachogram. The HRV was then computed using a frequency domain analysis, by means of the estimation of its PSD.

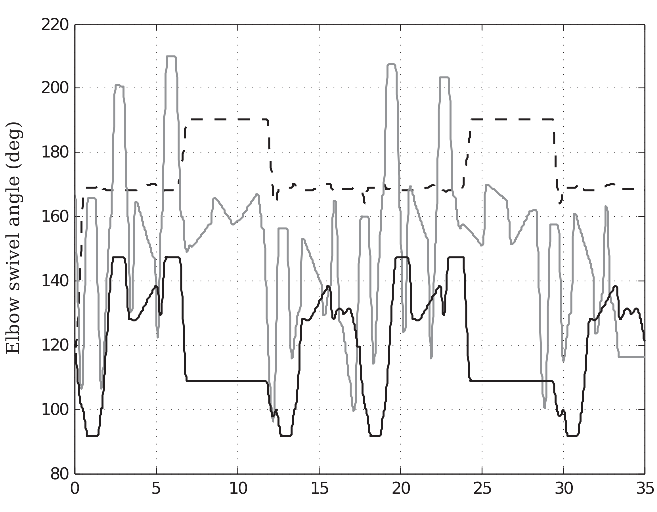

Fig. 5. Left elbow swivel angle during the three motions (HL: solid black, nHL: dashed black, nHLTV: solid gray).

Since the portion of each experiment related to a particular redundancy resolution scheme is very short in time, the tachogram was first re-sampled at 4 Hz, and the overall linear trend, corresponding to the VLF (Very-Low Frequency) bandwidth < 0.04 Hz, was removed. Then, following modern approaches in the analysis of the HRV signal, see e.g. (Carvalho et al., 2003), an AR (Auto Regressive) model of order 15 was identified using the well-known Yule–Walker equations. The PSD of HRV signal has been therefore estimated directly from the AR model coefficients, (Akaike, 1969), rather than applying the FFT (Fast Fourier Transform) to the HRV signal. This way a smoother PSD with a higher frequency resolution was obtained. Fig. 6 shows the frequency domain analysis of the HRV related to one of the experiments.

3.4.2. *Processing of the EMG signal*

While most of the existing methods to analyse EMG signals are related to muscular force estimation, this work is rather focused on stress assessment. For this reason, an accurate estimation of the intensity and of the total duration of each contraction is not considered here.

The analysis of the muscle activity developed in this work is based on the detection of the so called *onsets* and *offsets*, (Hodges and Bui, 1996). An onset is defined as the time interval during which the muscle is contracted, whereas an offset corresponds to a negligible muscle activity. In order to estimate whether the corrugator muscle was contracted (onset) or not (offset) a windowing approach was introduced. It was first noticed that the level of noise

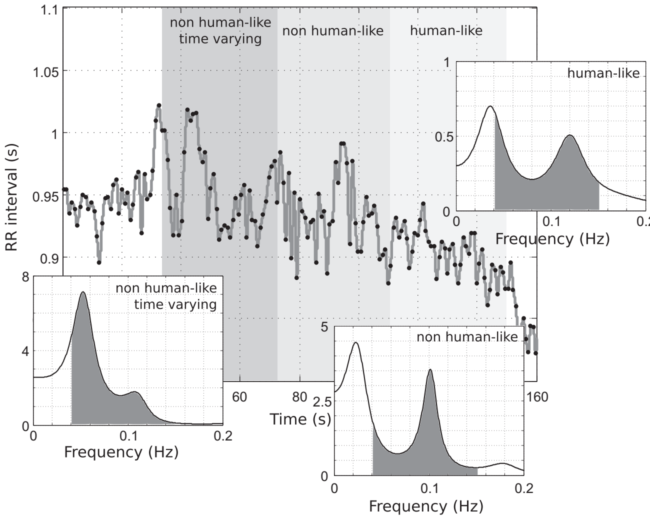

Fig. 6. Frequency components of the HRV PSD (the LF bandwidth is highlighted).

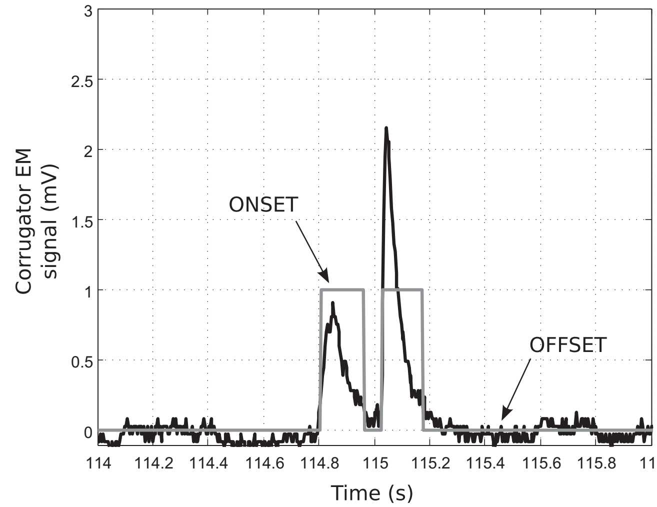

Fig. 7. Onsets extraction from RMS-EMG signal.

measured during the baseline acquisition was significantly lower with respect to the one measured during the actual experiment. Therefore, in order to remove the noise, the median of the entire acquisition was first measured and then removed from the acquired signal. Then, the IQR (Inter Quartile Range) was computed and used as an estimate of the noise amplitude. Finally, a candidate onset was recognized when EMG activity was greater or equal to 2.0 IQR for at least $\Delta t = 40$ ms. The onset recognition was then confirmed if the maximum level of the EMG signal was greater or equal to 3.0 IQR. The resulting onsets/offsets signal is shown in Fig. 7.

3.4.3. *Processing of the SCR signal*

The measured skin conductance has been first re-sampled at 16 Hz and then filtered with a Butterworth high-pass filer of order 6 with a cut-off frequency[2] of 0.04 Hz. This way, the DC level of the SC signal, which turned out to contain a significant drift, has been removed.

3.4.4. *Derived statistics from post-processed data*

In the following, the final analysis of the post-processed experimental data is reported. In particular, the definition of statistics aimed at quantifying the robot-induced stress is explained.

For the ECG signal, a common way to assess the dominance of the sympathetic nervous system with respect to the parasympathetic one, is to measure the ratio between the power associated to the two corresponding bands of frequency, (McCraty et al., 1995). Therefore, the following statistics was computed

$$s_{\mathrm{ECG}}^{i,\mathrm{RR}} = \frac{\mathrm{LF}^{i,\mathrm{RR}}}{\mathrm{HF}^{i,\mathrm{RR}}} \tag{2}$$

where

$$\begin{aligned} \mathrm{LF}^{i,\mathrm{RR}} &= \int_{0.04\mathrm{Hz}}^{0.15\mathrm{Hz}} \mathrm{PSD}^{i,\mathrm{RR}}(f)\mathrm{d}f \\ \mathrm{HF}^{i,\mathrm{RR}} &= \int_{0.15\mathrm{Hz}}^{\infty} \mathrm{PSD}^{i,\mathrm{RR}}(f)\mathrm{d}f \end{aligned} \tag{3}$$

while $i = 1, \ldots, 18$ and $\mathrm{RR} \in \{\mathrm{HL}, \mathrm{nHL}, \mathrm{nHLTV}\}$.

[2] Notice that the value 0.04 Hz is the same used for the VLF/LF separation in the HRV analysis.

As for the EMG activity of the corrugator muscle, the number of contractions per minute, regardless their duration and intensity, was counted:

$$s_{\mathrm{EMG}}^{i,\mathrm{RR}} = \frac{60}{t_f - t_0} \int_{t_0}^{t_f} \mathrm{edge}\left(\mathrm{onsets}^{i,\mathrm{RR}}(t)\right)\mathrm{d}t \tag{4}$$

where $\mathrm{edge}(\cdot)$ is a function returning a unit Dirac pulse corresponding to rising edges of the input.

For the analysis of the skin conductance, the following statistics has been considered:

$$s_{\mathrm{SCR}}^{i,\mathrm{RR}} = \frac{1}{t_f - t_0} \int_{t_0}^{t_f} \left(\mathrm{SCR}_{\mathrm{HighPass}}^{i,\mathrm{RR}}(t)\right)^2 \mathrm{d}t \tag{5}$$

which, apart from some scaling factors, corresponds, from Parseval's theorem, to the integrated PSD of the SCR over the frequency range $[0.04\,\mathrm{Hz}, \infty)$. Notice that the statistics introduced in (5) captures all the phasic SC features, i.e. the number of SCR (onsets), their intensity and duration, regardless the SCL and slowly-varying fluctuations which typically characterize tonic electro-dermal activity.

We finally introduce a robot-related statistics defining the average elbow elevation statistics:

$$s_{\mathrm{elbow}}^{\mathrm{RR}} = \frac{1}{t_f - t_0} \int_{t_0}^{t_f} z_{\mathrm{elbow}}^{i,\mathrm{RR}}(t)\mathrm{d}t \tag{6}$$

where $z_{\mathrm{elbow}}^{\mathrm{RR}}$ represents the instantaneous elevation of the elbow during the experiment.

4. Facts and results

For each statistics (EMG, ECG, and SCR) the Kruskal–Wallis ranking test was first performed to exclude possible correlation between the three groups (HL, nHL, and nHLTV). Figs. 8 and 9 report the boxplots of the normalized ECG and EMG statistics, respectively. At first glance, the ECG and the EMG statistics agree in predicting a clear trend. In order to obtain a more rigorous verification of this conjecture, the Page's L-test and the Jonckheere's trend test were computed for both the ECG and the EMG statistics.

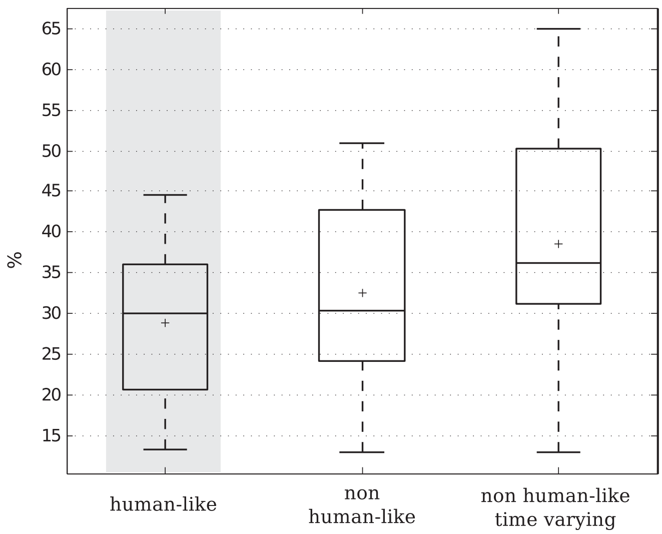

Fig. 8. Boxplot of the normalized ECG statistics.

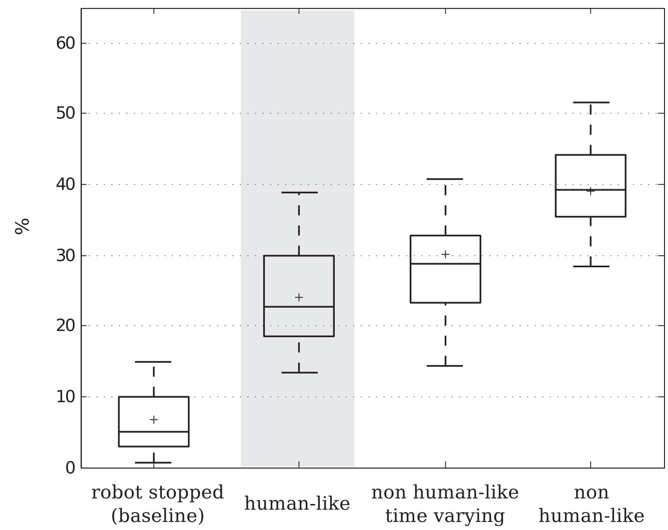

Fig. 10. Boxplot of the normalized SCR statistics corresponding to the alternative ordering of robot trajectories based on the average elbow elevation; reference level, corresponding to the absence of stimuli, is reported as first column.

The SCR statistics does not exhibit the same trend noticed for both the ECG and the EMG statistics, and deserves a more detailed discussion. For the SCR analysis, we here make use of a different ordering of the three robot trajectories by using the average elbow elevation statistics s_{elbow}, which results in the following order $s_{\text{elbow}}^{\text{HL}} < s_{\text{elbow}}^{\text{nHLTV}} < s_{\text{elbow}}^{\text{nHL}}$. Using this alternative order of the three motions, the resulting boxplot of Fig. 10 lends itself to a meaningful trend analysis. In fact, a positive trend of this statistics with respect to the average elbow elevation can be now reported. The Page's L-test and the Jonckheere's trend test were computed. The results of the two trend tests, as well as of the Kruskal–Wallis correlation analysis, are reported in Table 1.

5. Discussion

All the acquired physiological signals agree in highlighting perceived differences between the three groups of motions (Kruskal–Wallis test: EMG $p < 0.01$, ECG $p = 0.097$ and SCR $p < 10^{-5}$). This was somehow confirmed during the short interviews where the majority of the volunteers admitted to have noticed slight differences in the robot motion throughout the measurements.

As for the trend analysis, EMG and ECG signals produce the same increasing trend with respect to ordered groups (HL, nHL, nHLTV) with high significance (Page-L test: EMG $p \approx 0.05$ and ECG $p \approx 0.01$, Jonckheere's test: EMG $p < 0.01$ and ECG $p = 0.014$) meaning that there is an increased physiological activity during both the nHL and the nHLTV motions with respect to the HL motion, with higher values corresponding to the nHLTV scheme. The positive trend is more pronounced for the ECG signal with respect to the EMG signal, as also confirmed by the two p-values. Evidence that the HL motion is responsible of less pronounced physiological activity can be reported. Moreover, the jerkyness of the nHLTV trajectory seems to be responsible for an increased value of the LF/HF ratio, as well as a slightly observable intensification of facial muscular activity.

Concerning the SCR signal and the alternative order (HL, nHLTV, nHL), the increasing trend can be observed with statistical significance (Page-L test: $p < 0.001$, Jonckheere's test: $p < 10^{-4}$). Moreover, each redundancy resolution scheme has a higher level of electro-dermal activity with respect to the baseline (Mann-Whitney-Wilcoxon test: $p = 10^{-6}$, $p < 10^{-6}$, $p < 10^{-6}$, for HL, nHLTV,

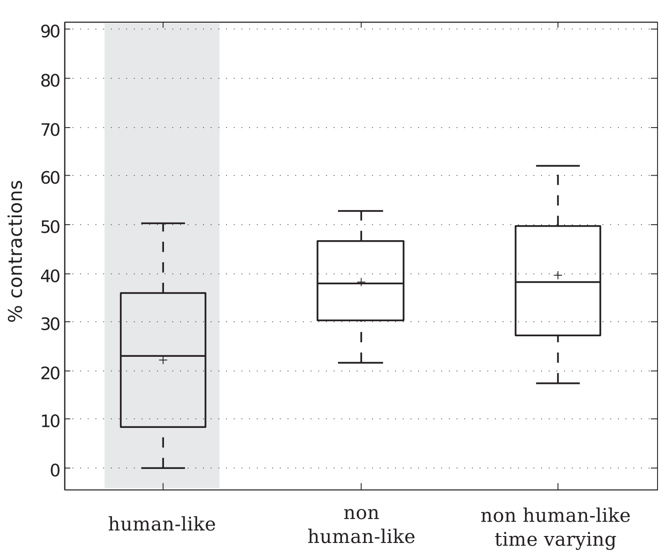

Fig. 9. Boxplot of the normalized EMG statistics.

Table 1
Results of the tests.

Signal	Statistics	Test	Meaning	Test results	
				Value	p-value
ECG	s_{ECG}	Kruskal–Wallis test	Uncorrelation analysis		0.097
		Page-L test	Positive trend analysis	230	≈0.01
		Jonckheere's test	Positive trend analysis	2.2063	0.0137
EMG	s_{EMG}	Kruskal–Wallis test			0.0054
		Page-L test		225	≈0.05
		Jonckheere 's test		2.8254	0.0024
SCR	s_{SCR}	Kruskal–Wallis test			$< 10^{-5}$
		Page-L test		515	< 0.001
		Jonckheere's test		4.2854	$< 10^{-4}$

nHL, respectively). An increased level of awareness can be reported for increasing value of elbow elevation, with maximum values corresponding to the nHL motion, characterized by the highest level of elbow elevation s_{elbow}. This fact was also reported during the interview by some of the volunteers, who declared to be surprised/uncomfortable due to the vicinity of the elbow to their face.

6. Conclusions

For the same assembly-like task performed by a dual-arm robot, the effects of three redundancy resolutions on a human fellow coworker were compared by means of physiological signals. The human-like redundancy resolution strategy, characterized by lower elbow elevations, induced a quantified reduction of the emotional arousal and was responsible for reduced EMG activity and LF to HF ratio on ECG signal. For these reasons, human-like motion profiles are the candidate to effectively reduce the robot-induced stress in human fellow co-workers, resulting in a more ergonomic interaction. Further and deeper investigations are still needed to address the effect of long-lasting exposition to robot motions.

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